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Natural Disasters, Self-Insurance and Human Capital Investment

Evidence from Bangladesh, Ethiopia and Malawi

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Abstract

This paper examines the impacts of disasters on dynamic human capital production using panel data from Bangladesh, Ethiopia, and Malawi. The empirical results show that the accumulation of biological human capital prior to disasters helps children maintain investments in the post-disaster period. Biological human capital formed in early childhood (long-term nutritional status) plays a role of insurance with resilience to disasters by protecting schooling investment and outcomes, although disasters have negative impacts on investment. In Bangladesh, children with more biological human capital are less affected by the adverse effects of floods, and the rate of investment increases with the initial human capital stock in the post-disaster recovery process. In Ethiopia and Malawi, where droughts are rather frequent, exposure to highly frequent droughts in some cases reduces schooling investment but the negative impacts are larger among children embodying less biological human capital. Asset holdings prior to the disasters, especially the household's stock of intellectual human capital, also helps maintain schooling investments at least to the same degree as the stock of human capital accumulated in children prior to the disasters.

This paper—a product of the Global Facility for Disaster Reduction and Recovery Unit, Sustainable Development Network Vice Presidency—is part of a larger effort in the network to disseminate the emerging findings of the forthcoming joint World Bank-UN Assessment of the Economics of Disaster Risk Reduction. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The team leader—Apurva Sanghi—can be contacted at "asanghi@worldbank.org", and the author of this paper at "f.yamauchi@cgiar.org". We thank Apurva Sanghi and participants at the World Bank for useful comments.

Natural Disasters, Self-Insurance and Human Capital Investment: Evidence from Bangladesh, Ethiopia and Malawi[1]

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1. Introduction

It has been increasingly recognized that growth in early childhood has long-term impacts on subsequent human capital formation and labor-market outcomes (e.g., Alderman et al., 2006; Hoddinott et al., 2008; Yamauchi, 2008). Disasters can dramatically reduce children's nutrient intake, leading to malnutrition and therefore lower formation of biological human capital in early childhood (e.g., Hoddinott and Kinsey, 2001; Del Ninno and Lundberg, 2005). However, many important questions have not been addressed or answered empirically.

We recognize that investment in human capital can take different forms, including investment in biological human capital (as in health and nutritional status) as well as in intellectual human capital (schooling and cognitive skills) (Behrman et al. 2008).

Once biological human capital is formed at the early stage, how resilient is it to the adverse impacts of disasters? Does it help maintain the formation of other forms of human capital, such as intellectual human capital acquired through schooling, at subsequent stages despite the occurrence of disasters? After disastrous distortions due to natural hazards, do healthy children recover faster? Or do disasters affect the inequality of attained intellectual human capital among children by differentially interrupting the formation of biological human capital? Do some types of human capital serve as insurance to protect the accumulation of other forms of human capital in the face of disasters?

The question of whether human capital is robust to natural hazards such as floods, droughts and earthquakes provides more extensive insights. First, in contrast to physical capital, human capital is portable and remunerable in different locations.[3] Therefore, agents can potentially avoid the damages to human capital unless natural hazards are extremely sudden and unexpected.

Second, biological human capital (especially health and attained height from adequate nutrient intake and other inputs into child health) accumulated prior to disasters raises the survival probability and resilience to disasters among both adults and children. Therefore, actual exposures to natural hazards (damages) depend on the stock of biological human capital accumulated in the pre-disaster period. For example, it is plausible that healthy children are less likely to become sick even in unsanitary environments immediately after disasters.

Third, after a disaster, the rate of investment in child schooling could depend on the pre-disaster stock of their health capital since the expected returns to schooling investment remain high among healthy children due to the complementarity between knowledge and health capital. That is, the accumulation of biological human capital prior to the disaster helps maintain the investment in a dynamic context. The convergence to the original path (recovery) is expected to be faster among children who already embody larger stocks of human capital. Moreover, if disasters are frequent, the

[3]Educated adult members can migrate to keep the returns to their human capital, e.g., urban labor markets, which help to mitigate the impacts of natural disasters on the household income. Children can also mobilize their human capital to different locations, but this strategy will decrease their subsequent human capital accumulation. However, if returns to human capital are high because of frequent natural hazards, the incentive to invest in human capital becomes strong, which can increase the accumulation of human capital in the long run despite negative effects of disasters on income (which decreases investments in human capital at least temporarily).

inequality of human capital may increase in the long run.[4]

The above second and third points imply the possibility of poverty traps. First, the impacts may be asymmetric between children with and without enough human capital.[5] Second, in the recovery process, human capital accumulation prior to disasters enables the continuation of human capital investment. That is, the inequality in the initial stock of human capital may exacerbate divergence in human capital accumulation owing to perturbations caused by natural hazards. Empirical analysis will test the above hypotheses.

In the empirical analysis of this paper, we use panel data from household surveys that the International Food Policy Research Institute has conducted in Bangladesh, Ethiopia and Malawi (see Del Ninno, et al., 2001; Gilligan and Hoddinott. 2005; Quisumbing, 2005; Sharma, 2005). Each country provides a natural experiment with natural hazards by which to test the above propositions. Bangladesh had a severe flood in 1998, and both Ethiopia and Malawi experienced large droughts in 2001 (followed by a flood in 2001-2002 in Malawi). Though in each country the initial round was conducted at different times, we have information on anthropometry for children aged below 60 months before or immediately after the disaster. Coupled with the information on child schooling in the post-disaster round, we can estimate transition equations of human capital formation from the pre-school to school stages. Among these countries, we observe differences in the pattern of natural hazards. Our data show that while the 1998 flood was a single severe event for many households in our sample in Bangladesh, droughts were rather frequent in Ethiopia and Malawi (among which the 2001 drought was the most severe).

The paper is organized as follows. The next section describes a simple model to describe how natural hazards affect human capital formation in the early childhood and school-age stages. Sections 3 and 4 discuss the econometric framework and data respectively.

In Section 5, the empirical results show that the accumulation of human capital prior to disasters helps children maintain investments in the post-disaster period. Biological human capital formed in early childhood (nutritional status) plays the role of insurance against disasters by increasing schooling investment and outcome, despite negative disaster impacts on the investment. In Bangladesh, children with more biological human capital are less affected by the adverse effects of the flood, and the rate of investment increases with the initial human capital stock in the recovery process after the disaster. In Ethiopia and Malawi where droughts are rather frequent, the exposure to highly frequent droughts in some cases reduced schooling investment but the negative impacts are larger among children embodying less biological human capital. However, asset holdings prior to the disasters, especially intellectual human capital stock in the household, also help maintain schooling investments to the same degree as the stock of human capital accumulated in children prior to the disasters.

[4]The inequality between the affected and non-affected areas must be conceptually separate from the inequality within the affected areas. Natural hazards increase the former, but not necessarily the latter as this depends on mechanisms through which disasters affect the dynamics of human capital formation.

[5]Recently macroeconomic literature shows the relationship between natural hazards and growth performance. In Noy (2008), the illiteracy level increases the negative impact of natural disasters on GDP growth.

2. A Simple Model

This section introduces a simple model in which parents decide on how much to invest in child biological human capital (health) and intellectual human capital (schooling), resulting in labor market returns (In our subsequent exposition, we use ”health” and ”biological human capital” interchangeably; similarly, we use the terms ”schooling,” ”knowledge capital,” and ”intellectual human capital” interchangeably as well.

For simplicity, we treat the age distribution of children as exogenous and assume that children enter the labor market in the final stage. Health is formed in the first stage[6], while schooling investment is undertaken in the next stage.

In the pre-school stage, per-capita consumption and shocks determine health capital h^1, $h^1 = f(c_1, D_1) + \varepsilon_1$ where c_1 is per-capita consumption in the household and D_1 is disaster measure in $t = 1$, and ε_1 is an idiosyncratic health shock. For simplicity, we assume that health capital accumulates only until age a^* when child enters the schooling stage. The investment component $f(c_1, D_1)$ is characterized by the properties: $\frac{\partial f}{\partial c_1} > 0$, $\frac{\partial^2 f}{\partial c \partial D_1} 0$ and $\frac{\partial f}{\partial D_1} < 0$. For simplicity, we assume that $c_1 = y(k, D_1)$, that is, income is exogenously determined by disaster occurrence and capital stock k in time 1.

At the second stage, knowledge capital h^2 accumulates with schooling investments s. The knowledge production function is given as

$$h^2 = g(s, h^1, D_2) + \varepsilon_2$$

where D_2 is the disaster measure in the second stage and s is investment in child schooling. Depending on the exact timing of disaster, D_2 can decrease or increase the marginal productivity of schooling investment. This relationship also depends on health capital. For example, healthy children can recover from disaster faster since the marginal value of time in school can increase faster in the catch-up period for healthy children, i.e., $\frac{\partial^2 g}{\partial s \partial D_2} > 0$. However, a disaster is also expected to directly decrease the formation of human capital through the destruction of school facilities and transportation infrastructure. In this case, the effectiveness of investment decreases with a disaster, $\frac{\partial^2 g}{\partial s \partial D_2} < 0$.

Complementarity between schooling and health is captured by $\frac{\partial^2 g}{\partial s \partial h^1} > 0$. The complementarity (or substitutability) implies that parents want to observe attained health capital among their children in order to optimally decide how to allocate schooling investments among them. Due to the sequential nature of human capital investment, parents can predict future outcomes of child human capital and their

[6]Nutrient intakes until the age of 3 are regarded as very important in forming child biological or health capital, measured by height-for-age Z-score. Although weight-for-age Z-score fluctuates over time (age) due to changes in nutrient intakes (that is, consumption) as well as morbidity, height-for-age Z-score is less likely to change after the age of 3. In the context of dynamic human capital production, therefore, child biological human capital is measured by the height-for-age Z-score.

labor-market returns from the outcomes of early-stage nutrition and health investments.[7] This intrahousehold issue is also important when we think about disaster impacts on child human capital because parents can endogenously control the impacts on children by adjusting resources among siblings.

The household budget constraint in the second stage is

$$c_2 + ps = y(k, D_2) + w(h^1, D_2)\left[T - s\right] + b(k, D_2)$$

where $w(h^1, D_2)$ is child wage, T is time endowment for the child, p is school fee, $b(k, D_2)$ is an intertemporal transfer conditional on disaster occurrence, and y is exogenous household income (determined by capital stock and disaster). It is assumed that child wage increases with health capital, that is, $w_h \geq 0$.[8] Assume that child cannot work during the pre-school stage, but can work in the labor market when he or she enters school.[9] Note that we treat $b(k, D_2)$ as exogenous, and the detail on this transfer will be discussed below.

Parents maximize the objective function

$$\max_s E\left[u(c_2) + \beta V\left(W(h^1, h^2) - b(D_2)\right) \mid h^1, D_2\right]$$

which captures the discounted sum of expected utilities from consumption over time and the final-period returns from children. The discount factor β has an interpretation of altruism to children, who have an increasing and concave utility function V. Assume that $W(h_1, h_2) = R_1 h_1 + R_2 h_2$ where R_1 and R_2 are financial returns to health and knowledge capital respectively. In this version, since we do not have uncertainty in the future returns to human capital, we omit the expectations operator below. If the wage function is strictly concave, parents have incentives to equalize human capital among their children.

Suppose that $b(k, D_2)$ is determined to equalize the discounted marginal utilities between the two periods. For example, agents also borrow cash from their relatives. For the sake of easing tractability, we assume that agents have to pay back in the next period after disaster recovery. In this setting, we have $\lambda^* = u'(c_2^*) = \beta V'(c)$ where λ^* is the

[7]Cunha et al. (2004) summarize some key concepts in the sequential development of child human capital. They focus on cognitive and noncognitive development. Their analysis does not directly include health and nutritional status as part of human capital in child development. The exclusion of health capital from the analysis results in a framework in which they can focus on human capital production function and complementarity and substitutability of different inputs (e.g., early childhood and schooling stage). Children also work in the labor market where health capital has economic returns. This institutional setting creates implications that offset the health-schooling complementarity effect.

[8]It is also important to note that the income opportunity in the child wage $w(h^1, D_2)$ is not necessarily related to labor markets. It may also capture activities such as child care and self-employment.

[9]Several reservations follow. First, we assume that income from siblings, parents, and credit are pooled in the household budget constraint and therefore are perfectly substitutable. Second, to describe the income process, the model does not assume a production function in which adult and child labor inputs are not perfectly substitutable. Third, the utility function does not include leisure, which is imperfectly substitutable between household members (e.g., Pitt and Rosenzweig, 1990).

Lagrange multiplier associated with the budget constraint. This condition means the marginal rate of intertemporal substitution is equal to unity.

The first order condition for schooling investment at the second stage is

$$u'(c_2^*)\left[w(h^1, D_2) + p\right] = \beta V'(c)\frac{\partial g}{\partial s}(s, h^1, D_2)R_2$$

That is,

$$w(h^1, D_2) + p = MRS * \frac{\partial g}{\partial s}(s, h^1, D_2)R_2$$

where $MRS = \frac{\beta V'(c)}{u'(c)}$. The income effect is captured by an increase in MRS with D_2, while the substitution effect is derived from a decrease in wage rate. As discussed, we do not know whether D_2 increases or decreases $\frac{\partial g}{\partial s}$. These conditions provide the schooling investment function $s = s(k, h_1, D_2)$. Note that at the first stage, the problem is trivial, since exogenous income and disaster shocks determine investment in health capital.

If $b(k, D_2)$ functions perfectly, MRS is constant. Therefore, we can ignore possible change of MRS. Otherwise, from the second order condition and the partial derivative of the s's first order condition with respect to D_2, we know that the effect of disaster on schooling investment depends on:

$$LHS = \frac{\partial w(h_1, D_2)}{\partial D_2} \leq 0.$$

and

$$RHS = MRS\frac{\partial^2 g(s, h_1, D_2)}{\partial s \partial D_2}R + \frac{\partial MRS}{\partial D_2}\frac{\partial g}{\partial s}(s, h_1, D_2)R.$$

Again the second term in RHS is zero if $b(k, D_2)$ functions perfectly. Schooling investment decreases if $RHS < LHS$.

Let us now examine the possible roles of health capital formed in the pre-disaster period. First, h^1 reduces the negative impact of disaster on the marginal productivity of schooling (cushioning the shock on schooling investment), and/or increases the marginal productivity of schooling investment when disaster occurs. We may call the latter a "recovery effect", which is characterized by the condition $\frac{\partial^2 g(s, h_1, D_2)}{\partial s \partial D_2} > 0$ with large h^1. After disaster, healthy children increase the rate of investment in schooling to catch up faster.[10]

[10]However, in general, a disaster is expected to decrease the effectiveness of schooling investment, for example, by destroying schools. In this case, $\frac{\partial^2 g(s, h_1, D_2)}{\partial s \partial D_2} < 0$. When we empirically observe $\frac{\partial^2 g(s, h_1, D_2)}{\partial s \partial D_2} > 0$ or

Second, if $b(k, D_2) = 0$, we have two direct effects of disaster on income. Disaster directly affects income generating activity ($y(k, D_2)$) and wage rate in the labor market ($w(h^1, D_2)$). These effects increase the marginal utility in the second stage, so decreasing MRS other conditions being equal. Schooling investment decreases if the income effect dominates.

Third, the LHS condition means a decrease in wage, which increases schooling investment. The question of real relevance is whether the labor-market effect is larger than the income reduction effect. Since labor is mobile and the labor market extends beyond the disaster-affected areas, it is reasonable to suppose that the labor-market effect is smaller than the income-reduction effect.

We included health capital in child wage function. Health capital can mitigate the shock on the wage rate. If the rationing in the labor demand becomes tougher during a period of disaster, it is possible that healthier children can find work more easily. So the negative effect of disaster on wage rate could be smaller for them.

The pre-disaster asset holding k can also mitigate the direct impact of disaster on income in the second stage in two ways. Asset holdings can be used as collateral for borrowing cash from the credit market ($b(k, D_2)$). Assets may also directly cushion the impacts of natural disaster, for example, by securing water supply with irrigation assets ($y(k, D_2)$).

Finally we may think about an interesting experiment under the condition $E[D_1 D_2] < 0$. In an extreme situation, let us consider two scenarios: case 1 - $D_1 = 1$, $D_2 = 0$, and case 2 - $D_1 = 0$, $D_2 = 1$. Case 1 implies smaller health capital embodied in the child. This decreases schooling investment if health capital and schooling investment are complementary. Case 2 implies more health capital in the first stage, but a disaster occurs in the second stage, affecting schooling investment. If agents know that shocks are negatively correlated over time and health capital can mitigate the negative impact of disaster on schooling, it is optimal to invest in the child's health capital in the first stage. In the model above, we assumed out decision making of nutrient intake but this dynamic intertemporal issue regarding health capital and schooling investment is an interesting issue to empirically investigate. For example, we predict that a higher probability of disasters in the future increases preventive investment in human capital in early childhood.

3. Econometric Framework

In this section we describe the econometric framework used to clarify the hypotheses to test the role of early-stage (biological) human capital in forming (intellectual) human capital stock in a dynamic context in the presence of disasters. We investigate the transition from early childhood nutrition/health status to schooling stages to examine how disasters affect human capital formation in the affected and unaffected

$\frac{\partial^2 g(s, h_1, D_2)}{\partial s \partial D_2} < 0$ depends on not only h_1 but also the actual timing of observation. For example, the impact is likely to be negative during and immediately after the disaster, but it can be positive once the recovery process begins. Therefore, the prediction depends on timeframe used in the analysis. In the above model, the second stage occurs nearly 10 years later in the life cycle.

areas. As discussed more carefully in the next section, the analysis utilizes data collected after actual natural disaster events: the 1998 flood in Bangladesh, and 2001 droughts in Ethiopia and Malawi.

As discussed in the previous section, the use of child schooling to measure disaster impacts may be potentially problematic since disasters may affect not only the marginal utility (due to income reduction) but also the opportunity cost of schooling investment (i.e., a decrease in labor-market wage). The former decreases schooling investment in order to smooth consumption over time, but the latter increases the investment since a decrease in the market wage increases the incentive to allocate more time to schooling. However, many disasters are different from economic recessions. For example, floods can destroy school facilities to disrupt normal school activities. Severe droughts - those analyzed in the Ethiopian and Malawi examples in this paper - cause substantial decreases in crop production, which threatens food security and human survival and therefore increases the real necessity for children to earn incomes for their families.

The focus of this paper is on the role of pre-school human capital in overcoming and recovering from the adverse impacts of disasters. As clarified in the model, recovery from disaster could be quicker if the child embodies large (biological) human capital prior to the disaster. Capturing this dynamic process empirically depends on the exact timing of data collection and disaster occurrence. Although the direct effect of a disaster on schooling (or child growth) is negative during and immediately after the disaster, once the recovery process begins, the experience of such a disaster may hasten the rate of investment in schooling. The empirical question is under what conditions the recovery process begins, and whether the negative impact of disaster persists over time.

We use years of grades completed to our measure of child schooling, with child height in the previous period as a key explanatory variable. Controlling for child height (our indicator of investments in biological human capital in early childhood), we look at human-capital growth from pre-school to school periods.

$$h^2_{ijl,,t+1} = \alpha + \beta_1 h^1_{ijl,t} + \beta_2 D_{jl} + \beta_3 D_{jl} h^1_{ijl,t} + \sum_k \beta^k_4 D_{jl} a^k_{jl0}$$
$$+village_l + age_i + \varepsilon_{ijl,,t+1} \qquad (1)$$

where $h^2_{ijl,t+1}$ is grades completed up to $t+1$ for child i in household j and village l, D_{jl} is disaster indicator (indexes) or its continuous measure such as repair cost, $h^1_{ijl,t}$ is child height in t, a^k_{jl0} is pre-disaster asset of type k, $village_l$ is the village fixed effect (this could be a wider geographic unit than village, depending on the empirical context), age_i denotes a set of age dummies to control for age-specific grade progression and $\varepsilon_{ijl,,t+1}$ is the error term. In the above notations, we used time 0 and 1 to denote pre-disaster asset (before t) and post-disaster public assistance (before $t+1$) respectively.

We assume that $E[\varepsilon_{ijl,t+1} a^k_{jl0}] = 0$. Pre-disaster assets are also uncorrelated with shocks to schooling investment in $t+1$. Also assume that $E[\varepsilon_{ijl,t+1} D_{jl}] = 0$, implying that the disaster occurred before $t+1$ and actions taken in $t+1$ are conditioned on this information.

Including village (area) fixed effects may underestimate the impacts of disaster if the shocks are perfectly correlated within a village. However, there is a cost of not including village fixed effects since unobserved village-specific factors often jointly affect child schooling in the village (e.g., change in school availability). Actual costs of flood and drought are not evenly distributed among villagers. In the analysis below, I estimate not only the direct impact of disaster but the indirect effects through pre-disaster child human capital and asset holdings, which mitigate the above problem.

One advantage of using village fixed effects is that we can control for possible substitution effects on child schooling through changes in the wage rate in the labor market if labor market conditions are homogeneous at least within the village (area). Therefore, with village fixed effects, we expect to observe negative effects of disaster on schooling (through income effects).

As discussed in the previous section, β_2 and β_3 could be either positive or negative. $\beta_3 > 0$ together with $\beta_2 < 0$ implies that the recovery process from a disaster is faster, if the child embodies more human capital in the previous stage (before disaster). If the recovery process is faster for children with more initial human capital, the process will increase inequality in human capital among children. $\beta_3 < 0$ implies that the disaster will decrease the inequality in human capital formation among children (or siblings). After a disaster, it is possible that $\beta_1 = 0$ if adverse impacts of disaster are large and/or destructive forces due to the disaster can entirely subvert the dynamic formation of human capital (for example, if all schooling and health facilities are destroyed).

4. Data

This section describes the data from Bangladesh, Ethiopia and Malawi that we use to test our hypotheses. The International Food Policy Research Institute has conducted panel household surveys in the three countries with corresponding local collaborators. The period covered in the panel data includes the occurrence of major natural hazards such as flood and drought.

In Bangladesh, the initial survey round was fielded in late 1998, immediately after the onset of the 1998 flood, followed by two subsequent rounds until the middle of 1999 (del Ninno et al. 2001). In 2004, a follow-up survey was conducted in April-May, coinciding with the season of the previous survey round, April-May 1999 (Quisumbing 2005a, 2005b).

In Ethiopia, the panel data set builds on the Ethiopian Rural Household Survey (cite), which began in a smaller sample of villages in 1989, then was expanded to 15 villages in 1994. Several rounds were conducted before 1999. For child anthropometry data, we use the 1997 round. A large drought occurred in 2001, followed by the 2004 survey. Similarly, in Malawi, the initial round occurred in 2000, followed by the 2001 drought and the subsequent round in 2004. Therefore, combining the panel data and the information on these natural hazards, we have an ideal setting to assess the impacts of natural hazards and disasters on human capital formation and the roles of ex-ante actions and ex-post responses.

However, the exact timing of the natural hazards and surveys matter in interpreting our empirical results, although we adopt the unique approach described in the previous sections. In Bangladesh, the initial survey round was fielded almost immediately after the 1998 flood. Though effects of the disaster were gradually realized after the flood, the initial round would already have captured some of the effects of flood exposure. The subsequent two rounds conducted within a year captured dynamic changes of the disaster's impact. This issue is especially important in child anthropometry, if malnutrition led to child weight loss soon after the flood.[11] Therefore, the interpretation of the empirical results needs special attention. However, we think that child height is more robust than child weight to shocks.[12] For pre-flood assets, however, the data were constructed to reflect the pre-flood situation.

In contrast, the initial survey rounds in Ethiopia and Malawi took place before the 2001 droughts. Thus, the information on child schooling and anthropometry are not contaminated by the influence of the droughts (except the parts explained by ex-ante actions). However, potential problems arise from the interval between the 2001 droughts and the 2004 follow-up survey. Given that the actual impacts on income that are supposed to have occurred in 2001-2002, the interval between the drought and the 2004 survey was rather short. This means that we may not capture the recovery process of human capital investment in the two-year period.

Malawi had a large flood in 2001-2002 after the 2001 drought. However, our preliminary analysis indicates that the impacts of the flood were rather small, compared to the drought. Therefore, we focus on the 2001 drought in Malawi for the empirical analysis. The above concern on the interval between natural hazards and the follow-up survey also holds.

Differences in the time structure of the hazards and the initial and follow-up rounds change the way in which we interpret empirical results. In Bangladesh, first, we may underestimate the initial impacts on child human capital since the first round, immediately after the flood, already contained some of the most immediate impacts. However, this survey is ideal for capturing the recovery dynamics of human capital starting immediately after the flood. Second, in Ethiopia and Malawi, the setting is suitable to investigate the short-run impacts on human capital investment as the interval between the droughts and the follow-up survey was rather short.

Third, in Bangladesh, using the three rounds conducted in a year after the flood, we can reveal short-term changes of child anthropometry after the flood, though the initial round could include some of immediate adverse impacts of the flood. Overall, the Bangladesh setting provides both long-term and short-term dimensions.

The 2004 surveys conducted in all three countries have retrospective information on past disasters. This is useful for knowing the frequency of disasters that households experienced until 2004. The frequency is defined as the empirical average of incidences in the period from the initial to the last round. This preliminary work showed that Ethiopia and Malawi experienced several droughts between the initial and follow-up rounds. In Bangladesh, however, the 1998 flood was the single most devastating

[11]Similarly, grades completed were not affected at the initial round, but attendance rate (in term of days attended per the total number of school days) could be already changed after the flood.
[12]Child weight is sensitive to short-term morbidity, which is an issue in the case of floods. Water-borne diseases and diarrhea typically increase in the aftermath of a flood. In the analyses, we use the height-for-age z scores in the range of -6 to 6.

incident for many households in our sample.[13] Standardizing the frequencies by the interval between the initial round and the 2004 follow-up survey, we have the following distributions for the three countries (Table 1).

Table 1 to be inserted

Because the 1998 flood was unusual in its severity and duration, in Bangladesh, instead of using a disaster measure based on frequency of occurrence, we use a flood exposure index that measures the severity of the flood (Del Ninno, et al. 2001). In this measure, exposure was grouped into none, moderately exposed, severely exposed and very-severely exposed. In addition, the Bangladesh data provide some details of the flood impacts such as the depth of water, the number of days covered by water, repair cost and the number of days evacuated from home. The former two measures are objective, but the latter two could be endogenous. Repair cost is an actual expenditure, so this involves household decisions and also depends on their asset holdings. The number of days evacuated is correlated with number of days covered by water, but it also measures the duration of staying safely away from the disaster, so it increases among those who had resources to relocate temporarily away from the flood (e.g., evacuating to other regions). Though these measures principally capture the disaster impacts, we may need to be careful in interpreting the results.

5. Empirical Results

5.1. Flood Impacts on Nutritional Status - Bangladesh

From the 1998 flood in Bangladesh, we can investigate the short-run impacts on child weight within a year after the flood. As described in the previous section, the 1998 survey started immediately after the flood, and traced individuals for a year with three rounds of data collection. The analysis uses rounds 1 and 3 to compute changes in weight-for-age and weight-for-height z scores. Flood exposure is measured by water depth, the number of days covered by water, repair costs and the number of days they were evacuated out of their homes (discussed in the previous section). Table 2 reports the estimation results.

Table 2 to be inserted

Columns 1 to 4 show the impacts on change in the weight-for-age z scores. The estimation controls for union fixed effects (rather than villages) to maintain a reasonable number of observations within the unit. Due to the sampling frame, we have only several households per village, which reduces the number of children below 60 months per village. Both the number of days submerged and repair cost have significant negative effects on weight-for-age z scores.

In Columns 5 to 8, we use the weight-for-height z scores. An increase in repair

[13] Floods are a normal part of the agricultural cycle in Bangladesh. However, the 1998 floods were exceptional both for their severity and duration. Unlike normal floods, which cover large parts of the country for several days or weeks during July and August, the 1998 floods lasted until mid-September in many areas, covering more than two-thirds of the country, causing over 2 million metric tons of rice crop losses (equal to 10.45 percent of target production in 1998/99) (del Ninno et al. 2001).

cost reduces the weight-for-height z score. However, the number of days evacuated from home is positively associated with the weight-for-height z score. It is possible that children, who had been evacuated from the affected areas, grew better than those who could not.

Our results summarized in Table 2 demonstrate impacts of the 1998 flood on changes in the child's anthropometric measures, consistent with other studies (e.g., Alderman et al., 2006). In the preliminary analysis, we could not find significant impacts on changes in the height-for-age z score in the one-year period.

5.2. Human Capital vs. Disasters

In this subsection, we summarize the dynamic impacts of disasters on the transition from early childhood to schooling stages using flood and drought examples in Bangladesh, Ethiopia and Malawi. As discussed in Section 3, we use the height for age z score to capture pre-school biological human capital, which reflects nutrient intake and health inputs during early childhood.

5.2.1. Bangladesh

In Bangladesh, this measure is obtained from round 1 in 1998, which was collected immediately after the flood. While one could argue that floods could immediately affect nutritional status, since height was measured right after the flood, the endogeneity issue is negligible. This is also one advantage of using the height for age z score, which is different from the weight for age z score as weight can fluctuate substantially in a relatively short period. In Ethiopia and Malawi, since the height for age z scores were taken from the initial round before the drought occurred, the above concern is not so important (see also discussions in Section 3).

Table 3 to be inserted

In Table 3, we use water depth, the number of days covered by water, repair cost and the number of days evacuated from home as measures of flood exposure. The dependent variable is years of grades completed in 2004. Column 1 shows a benchmark result on the height effect on grades completed. The height for age z score has a significant and positive effect on grades completed. The specification includes union fixed effects and age dummies.

Columns 2 to 5 show the effects of flood and child height on schooling. First, we confirm that even with flood variables, the height for age z score has significantly positive effects on schooling. Second, interestingly, flood measures have positive effects on schooling (after six years). Water depth and the number of days submerged show significant positive effects on schooling. Third, we do not observe significant interaction terms of flood and the height z score.

Note that these findings seem contradictory to those on the short-term changes in child's weight. Here we are looking at the outcome nearly 6 years after the flood. Therefore, if the recovery (catch-up) process started sometime before 2004, it is possible to observe that those who were affected could grow faster under certain conditions.

Table 4 to be inserted

Table 4 uses alternative measure of flood exposure, constructed by the IFPRI research team (Del Nino et al., 2001). The results are consistent with those in Table 2. First, in Column 1, the height for age z score has a significant and positive effect on schooling at a later stage. Having been severely exposed to flood significantly increased schooling within the same union. Second, in Column 2, healthy children (measured by the height for age z score) achieve more schooling if they had experienced severe exposures to the flood. We do not observe a significant direct effect of the height for age z score, but this was significantly influencing schooling through the flood severity.
In Columns 3 to 5, we check robustness of these findings by altering the range of the height z score for estimation. To maintain a reasonable number of observations in each estimation, the ranges overlap in these exercises. It shows that for children with relatively large height for age z scores, we find positive effects of the 1998 flood and interaction terms with the height for age z score. That is, healthy children experience a faster recovery from the disaster in the subsequent 6 years.

Tables 5 and 6 to be inserteed

In Tables 5 and 6, we investigate how pre-disaster assets affect the flood impacts on schooling, together with the early-stage human capital. We use total asset value, maximum education (years of schooling) in the household, land size, household size, and livestock value to represent asset allocation (holding) before the disaster. The maximum education measure covers children as well, so we include older siblings who may affect income smoothing at the household level. First, Column 1 in Table 5 confirms the previous result that the flood severity increases the subsequent investment in child schooling-that is, households who are most severely affected by the flood invest more in child schooling. In addition, the more assets they hold, the larger the positive impact of the flood on schooling investments. This suggests that households with more assets are better able to play ”catch up” with respect to human capital investments. In Column 2, we use more disaggregated measures of household assets. Interestingly, investments in human capital after the flood are higher for households with higher maximum education. However, with the inclusion of these asset variables, the height effects and direct effects of the flood become insignificant.

In Table 6, we use water depth, the number of days submerged, repair cost and the number of days evacuated from home to measure the 1998 flood exposure. The results are qualitatively similar. First, the height effect is robust to various measures of flood exposure in all estimations. Second, total asset value increases the catch up effect on human capital investment after the flood in the specification with the number of days covered by water Third, and more dramatically, the maximum education within the household significantly increases the positive impact of the flood in Columns 5 to 8.

These results imply substitution between the early-stage child human capital and the household asset holding in the sense that households may choose one of the two to mitigate (increase) the flood impact on schooling in a dynamic context. In the Bangladesh example, our results showed a post-disaster recovery process in the 6-year period, with asset holdings and human capital within the household contributing positively to the recovery process after the flood.

5.2.2. Ethiopia

Tables 7 and 8 summarize estimation results for Ethiopia. In our preliminary analysis, we have found that although the 2001 drought has the most widespread exposure, the country had also experienced many other, smaller-scale, droughts. Therefore we assess the impacts of both the 2001 drought and drought frequency on child schooling. Therefore, not only the 2001 drought indicator, but also the average likelihood (frequency) of droughts in the period 1999 to 2004 are used in the analysis.

Table 7 to be inserted

Column 1 in Table 7 shows that the height for age z score has a significant and positive effect on schooling. In Column 2, the estimation controls for household fixed effects, which confirms that the above finding remains robust even despite upward bias in the estimate. Column 3 adds the 2001 drought indicator, which shows that the drought had a negative impact on child schooling (marginally significant).

In Columns 4 and 5, we include interaction terms of drought(s) and the height z score. First, the 2001 drought indicator as well as the drought likelihood (two of three) have significant and negative effects on grades completed. Second, it seems likely that healthier children (i.e. taller) had experienced larger negative impacts from droughts than less healthy children. This result is contrary to those found in Bangladesh probably due to the difference in timeframe. This result implies that the inequality of human capital among children has decreased with the frequent exposure to droughts.

Columns 6 and 7 split the sample based on the ranges of the height z score. To maintain reasonable numbers of children in both estimations, the ranges overlap. The results show that the negative impacts of droughts are larger among children embodying less biological human capital in early childhood. This is consistent with our hypothesis (also confirmed in the Bangladesh example) that human capital accumulation prior to disasters increases resilience to the adverse effects of disasters.

Table 8 to be inserted

Table 8 reports results on asset effects. As in Bangladesh, we used total asset value, maximum education (years of schooling) in the household, land size, household size and livestock value. Column 1 shows the total asset effect with the 2001 drought indicator. Interestingly, the negative impact of the drought is magnified by asset level. Wealthier households (as measured by the total asset value) experienced larger negative drought impacts on child schooling than poorer households. Again, the height effect remains robust with the drought indicator. Column 2 similarly shows that land size magnifies the negative impact of drought on child schooling.

Columns 3 and 4 use the empirical frequency of droughts, interacted with household assets. At the low levels of drought frequency, direct effects of the droughts are significantly negative. However, this negative effect is significantly magnified by asset level, especially land size, if droughts are very frequent in the period of 1999-2004. However, holding livestock and a larger household size seem to help mitigate the negative drought impacts.

In all estimations, the height for age z score has significantly positive effects on schooling, though only highly frequent droughts decrease the positive effect.

5.2.3. Malawi

Tables 9 and 10 summarize estimation results for Malawi, using the same specification as Ethiopia. In Malawi, we focus on the 2001 drought. Although this drought was followed by a flood in 2001-2002, our preliminary analysis showed that the flood had insignificant impacts so we decided to focus on the 2001 drought.

Tables 9 and 10 to be inserted

In Table 9, we examined how the height for age z score affects drought impacts on child schooling. The results in Columns 1 to 4 show that the height effect is very robust to the drought, but the drought (and its likelihood of occurrence) does not have significant effects on schooling. This result remains the same even if we use the drought frequency (Table 10).

In Columns 5 and 6, we split the sample based on the ranges of the height z score. Interestingly, we observe a clear contrast between the two groups. Children who embody less human capital experienced significantly negative impacts of droughts. The increased frequency of droughts significantly reduces schooling completed. Moreover, a higher frequency of droughts decreases the positive effect of the height for age z score. In contrast, we observe significantly positive effects of droughts among healthy children (with greater height for age z scores), suggesting that healthier children are better able to invest in human capital after a disaster. This result also supports our proposition that the accumulation of human capital prior to disasters prevent adverse impacts on human capital formation.

6. Conclusion

This paper examined the impacts of disasters on dynamic human capital production using panel data from Bangladesh, Ethiopia and Malawi. Empirical results showed that the accumulation of (biological) human capital prior to disasters helps children maintain investments in intellectual human capital in the post-disaster period. Human capital formed in early childhood (nutritional status, proxied by height for age z scores) plays a role of insurance with resilience to disasters by increasing schooling investment and outcomes, despite negative disaster impacts on the investment itself.

In Bangladesh, children with more biological human capital are less affected by the adverse effect of the flood, and the rate of investment in intellectual human capital increases with the initial human capital stock after the disaster, achieving a faster recovery. In Ethiopia and Malawi where droughts are rather frequent, the exposure to highly frequent droughts reduced growth and inequality of human capital. Human capital stock helps maintain investments in the long run, though highly frequent shocks disrupt subsequent investments. In all countries, our evidence shows that children embodying more human capital prior to disasters are resilient to the disasters and experience a faster recovery.

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Table 1 Estimates of future disaster probabilities

Number of incidences:	None	Once	Twice	Three times
Bangladesh: Flood	0	0.14	0.29	
	(453)	(323)	(7)	
Ethiopia: Drought	0	0.20	0.40	0.60
	(594)	(394)	(215)	(54)
Malawi: Drought	0	0.25	0.50	0.75
	(389)	(228)	(101)	(36)

Numbers of households are shown in parentheses. Probabilities are defined as the empirical average of disaster incidences (measured yearly) in the period between the initial round and the final round.

Table 2 Short-run effects of Bangladesh flood on child weight

Dependent: Change in	Weight z score from round 1 to 3				Weight for height z score form round 1 to 3			
Flood variable:	Depth	Days	Repair cost	Outhome	Depth	Days	Repair cost	Outhome
Flood	-0.0425	-0.0060	-0.0001	-0.0006	-0.0414	-0.0030	-0.0001	0.0043
	(1.050)	(1.890)	(2.100)	(0.290)	(0.790)	(0.750)	(1.970)	(2.070)
Union FE	yes	yes	yes	yes	yes	yes	yes	yes
Number of obs	272	272	272	272	256	256	256	256
Number of union	21	21	21	21	21	21	21	21
R squared (within)	0.0281	0.0441	0.0456	0.0239	0.0209	0.0213	0.0287	0.0231

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Female indicator and age dummies are included in all specifications.

Table 3 Dynamic effects of Bangladesh flood on human capital formation

Dependent:					
Flood variable:		Depth	Days	Repair cost	Outhome
Haz 1998	0.1628	0.0839	0.0920	0.1495	0.1450
	(3.270)	(2.220)	(2.780)	(2.880)	(3.090)
Flood		0.2299	0.0083	0.0002	0.0014
		(2.840)	(1.820)	(1.040)	(0.210)
Flood * haz 1998		0.0413	0.0022	0.0007	0.0019
		(1.410)	(1.690)	(0.900)	(0.970)
Union FE	yes	yes	yes	yes	yes
Number of obs	209	209	209	209	209
Number of union	20	20	20	20	20
R squared (within)	0.3528	0.3846	0.3690	0.3595	0.3600

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Female indicator and age dummies are included in all specifications.

Table 4 Dynamic effects of Bangladesh flood on human capital formation 2

Dependent: Grades completed in 2004			-6<Haz<-2	-4<Haz<0	-2<Haz<6
Haz	0.1547	0.0516	0.1043	0.1396	0.0025
	(3.850)	(1.080)	(0.380)	(1.750)	(0.050)
Flood exposure 1	-0.1508	-0.1299	-0.3402	-0.1865	-0.2422
	(0.860)	(0.560)	(0.330)	(0.560)	(1.150)
Flood exposure 2	0.1719	0.5828	1.0593	0.8516	0.4078
	(1.550)	(2.480)	(1.080)	(2.310)	(1.600)
Flood exposure 3	0.4153	0.7200	-0.7561	0.9511	1.0040
	(2.490)	(2.250)	(0.490)	(2.920)	(3.720)
Haz * flood 1		0.0311	0.0578	0.0404	-0.0387
		(0.400)	(0.170)	(0.440)	(0.290)
* flood 2		0.1953	0.4228	0.2750	-0.0093
		(2.180)	(1.330)	(1.750)	(0.050)
* flood 3		0.1706	-0.1178	0.3691	0.0761
		(1.620)	(0.250)	(2.940)	(0.530)
Union FE	yes	yes	yes	yes	yes
N obs	209	209	118	179	90
N union	20	20	18	18	19
R squared (within)	0.3729	0.3862	0.3262	0.4165	0.5527

Numbers in parentheses are absolute t values using robust standard errors with union clusters.

Table 5 Dynamic effects of Bangladesh flood on human capital formation 3

Dependent: Grades completed in 2004				
Haz	0.0504	1.060	0.0552	1.050
Flood exposure 1	-0.2591	1.150	-0.3636	0.890
Flood exposure 2	0.5278	1.870	-0.0131	0.030
Flood exposure 3	0.6520	1.930	-0.3589	0.650
Haz * flood exposure 1	0.0238	0.310	-0.0268	0.350
Haz * flood exposure 2	0.1892	2.040	0.1750	1.520
Haz * flood exposure 3	0.1733	1.650	0.1074	1.020
Total asset * flood exp 1	2.56E-06	2.000		
* flood exp 2	8.59E-07	0.570		
* flood exp 3	1.94E-06	2.050		
Max educ * flood exp 1			0.0666	1.960
* flood exp 2			0.1078	2.140
* flood exp 3			0.0936	3.080
Land * flood exp 1			-0.0007	0.830
* flood exp 2			-0.0002	0.300
* flood exp 3			-0.0043	2.450
Household size * flood exp 1			-0.0381	0.570
* flood exp 2			-0.0169	0.220
* flood exp 3			0.1097	1.180
Livestock * flood exp 1			2.03E-06	0.120
* flood exp 2			0.00003	0.600
* flood exp 3			7.92E-06	0.350
Union FE	yes		yes	
N obs	209		209	
N union	20		20	
R squared (within)	0.3923		0.4360	

Numbers in parentheses are absolute t values using robust standard errors with village clusters. Female indicator and age dummies are included in all the specifications.

Table 6 Dynamic effects of Bangladesh flood on human capital formation

Dependent:								
Flood variable:	Depth	Days	Repair cost	Outhome	Depth	Days	Repair cost	Outhome
Haz 1998	0.0856	0.0922	0.1490	0.1516	0.1037	0.1174	0.1597	0.1727
	(2.240)	(2.870)	(2.880)	(3.190)	(2.410)	(2.900)	(2.890)	(3.160)
Flood	0.2071	0.0072	0.0002	0.0027	0.0459	-0.0068	-0.0001	-0.0077
	(2.410)	(1.500)	(1.010)	(0.440)	(0.450)	(1.340)	(0.240)	(0.420)
Flood * haz 1998	0.0401	0.0021	0.00008	0.0007	0.0284	0.0012	0.00007	-0.0003
	(1.380)	(1.590)	(1.020)	(0.290)	(0.910)	(0.770)	(0.820)	(0.190)
Flood * asset	3.59E-07	4.46E-08	2.28E-09	-3.57E-07				
	(1.150)	(2.420)	(1.170)	(1.160)				
Flood * max educ					0.0243	0.0012	0.00005	0.0028
					(3.280)	(2.040)	(2.260)	(1.630)
Flood * land					-0.0002	-2.74E-06	-1.65E-06	-0.0002
					(0.740)	(0.230)	(0.710)	(1.170)
Flood * household size					0.0111	0.0014	0.00003	0.0005
					(0.730)	(1.720)	(0.540)	(0.160)
Flood * livestock					-1.87E-07	1.66E-07	-2.06E-08	-3.15E-06
					(0.030)	(0.750)	(0.440)	(3.690)
Union FE	yes	yes	yes	yes	yes	yes	yes	yes
Number of obs	209	209	209	209	188	188	188	188
Number of union	20	20	20	20	20	20	20	20
R squared (within)	0.3868	0.3742	0.3627	0.3651	0.4087	0.3891	0.3634	0.3527

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Female indicator and age dummies are included in all specifications.

Table 7 Dynamic effects of Ethiopia drought on human capital formation

Dependent: Grades completed in 2004							
						-6<Haz<-1	-3<Haz<6
Haz	0.1447	0.1576	0.1346	0.1596	0.1551	0.1144	0.1395
	(3.110)	(2.980)	(3.160)	(3.890)	(2.820)	(1.460)	(1.270)
Drought			-0.2283	-0.4012			
			(1.740)	(2.140)			
Freq drought 1					-0.6048	-0.7567	-0.6637
					(6.110)	(2.120)	(4.550)
Freq drought 2					-0.3817	-0.8730	-0.5127
					(1.270)	(1.490)	(1.710)
Freq drought 3					-0.6378	-1.8844	-0.8819
					(3.910)	(4.150)	(4.530)
Haz * drought				-0.0835			
				(1.660)			
Haz * freq_drought 1					-0.0514	-0.0345	-0.0936
					(0.850)	(0.330)	(0.810)
Haz * freq_drought 2					-0.0413	-0.1527	0.0254
					(0.570)	(1.090)	(0.290)
Haz * freq_drought 3					-0.3013	-0.7965	-0.0559
					(2.850)	(3.830)	(0.330)
Peasant association FE	yes		yes	yes	yes	yes	yes
Household FE		yes					
N obs	314	314	303	303	303	238	206
N villages	14	143	14	14	14	14	14
R squared (within)	0.1800	0.2134	0.1852	0.1889	0.2053	0.1899	0.2041

Numbers in parentheses are absolute t values using robust standard errors with village clusters.
Male indicator and age dummies are included.

Table 8 Dynamic effects of Ethiopia drought on human capital formation

Dependent: Grades completed in 2004				
Haz	0.1968 2.430	0.1825 2.140	0.1901 1.890	0.1766 1.730
Drought	-0.4115 1.470	0.2387 0.400		
Haz * drought	-0.1101 1.410	-0.0648 0.970		
Freq drought 1			-0.9498 2.730	-0.3970 0.800
Freq drought 2			-0.5109 1.180	-2.2311 3.610
Freq drought 3			-0.4469 1.170	n.a
Haz * freq drought 1			-0.1358 1.020	-0.1401 1.000
Haz * freq drought 2			0.0331 0.450	0.0629 0.560
Haz * freq drought 3			-0.4032 3.810	-0.4119 1.410
Total asset * drought	-0.0006 2.160			
* freq_drought 1			0.0003 1.060	
* freq_drought 2		.	-0.0007 1.140	
* freq_drought 3			-0.0079 4.780	
Max educ * drought		-0.0471 1.090		
* freq_drought 1				0.0111 0.550
* freq_drought 2				-0.0403 0.430
* freq_drought 3				-0.0964 1.530
Land * drought		-0.2898 2.040		
* freq_drought 1				-0.1186 1.480
* freq_drought 2				-0.2216 1.270
* freq_drought 3				-3.2820 4.280
Household size * drought		-0.0154 0.210		
* freq_drought 1				-0.0552 0.900
* freq_drought 2				0.2245 1.840
* freq_drought 3				0.0354 0.440
Livestock* drought		8.61E-06 0.260		
* freq_drought 1				5.21E-06 0.180
* freq_drought 2				0.0004 3.110
* freq_drought 3				0.0009 0.630
Union FE	yes	yes	yes	yes
N obs	166	160	166	160
N peasant association	14	14	14	14
R squared (within)	0.0959	0.0965	0.1277	0.1972

Numbers in parentheses are absolute t values using robust standard errors with peasant association clusters. Male indicator and age dummies are included.

Table 9 Dynamic effects of Malawi drought on human capital formation

Dependent: Grades completed in 2004						
					-6<Haz<-1	-3<Haz<6
Haz	0.0991	0.1024	0.1412	0.1580	0.3962	-0.0304
	(2.610)	(2.760)	(2.290)	(1.920)	(3.590)	(0.390)
Drought		0.1196	-0.1518			
		(0.950)	(0.720)			
Freq drought 1				-0.2949	-0.9321	-0.1167
				(1.220)	(1.860)	(0.640)
Freq drought 2				-0.3396	-0.7459	-0.0021
				(1.240)	(1.910)	(0.010)
Freq drought 3				-0.6638	-4.8691	0.7905
				(1.120)	(3.630)	(3.160)
Haz * drought			-0.0790			
			(0.910)			
Haz * freq_drought 1				-0.1110	-0.3262	0.0986
				(1.100)	(1.920)	(0.920)
Haz * freq_drought 2				-0.0348	-0.1917	0.2316
				(0.300)	(1.160)	(1.730)
Haz * freq_drought 3				-0.1164	-1.2948	0.9312
				(0.600)	(3.450)	(8.140)
EA FE	yes	yes	yes	yes	yes	yes
Age dummies	yes	yes	yes	yes	yes	yes
N obs	153	153	153	153	117	115
N EA	40	40	40	40	38	38
R squared (within)	0.1092	0.1170	0.1328	0.1401	0.2548	0.1591

Numbers in parentheses are absolute t values using robust standard errors with EA clusters. Male indicator and age dummies are included.

Table 10 Dynamic effects of Malawi drought on human capital formation

Dependent: Grades completed in 2004				
Haz	0.1441 2.290	0.1478 2.210	0.1531 1.900	0.1524 1.770
Drought	-0.1275 0.710	-0.1422 0.410		
Freq drought 1			-0.4651 2.050	-0.7350 1.690
Freq drought 2			-0.4036 1.650	-0.7895 1.960
Freq drought 3			1.8928 4.380	n.a.
Haz * drought	-0.0746 0.870	-0.0655 0.730		
Haz * freq drought 1			-0.1308 1.330	-0.1203 1.180
Haz * freq drought 2			0.0156 0.140	0.0408 0.400
Haz * freq drought 3			0.3419 2.800	-0.1524 1.770
Total asset * drought	0.00002 3.130			
* freq_drought 1			0.00002 2.480	
* freq_drought 2			0.00003 2.910	
* freq_drought 3			-0.0003 6.250	
Max educ * drought		0.0101 0.280		
* freq_drought 1				0.0434 1.420
* freq_drought 2				-0.0504 0.990
* freq_drought 3				-0.0117 0.250
Land * drought		-0.0099 0.210		
* freq_drought 1				-0.0211 0.360
* freq_drought 2				0.0022 0.060
* freq_drought 3				n.a.
Household size * drought		0.0167 0.520		
* freq_drought 1				0.0218 0.580
* freq_drought 2				0.1181 3.370
* freq_drought 3				-0.0166 0.280
Livestock * drought		-5.53E-07 0.060		
* freq_drought 1				8.93E-07 0.190
* freq_drought 2				0.00007 1.980
* freq_drought 3				-0.0003 6.360
EA FE	yes	yes	yes	yes
N obs	152	148	152	148
N EA	40	40	40	40
R squared (within)	0.1538	0.1348	0.2217	0.2336

Numbers in parentheses are absolute t values using robust standard errors with EA clusters. Male indicator and age dummies are included.